5-12-2023

The effect of four decades of deregulation on competition and productivity of the U.S. freight transportation industry

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A Thesis
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Master of Science
in Civil Engineering
in the Richard A. Rula School of Civil and Environment Engineering

Mississippi State, Mississippi

May 2023

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Date of Degree: May 12, 2023

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Major Field: Civil Engineering (Transportation Engineering Concentration)

Committee Chair: Li Zhang

Title of Study: The effect of four decades of deregulation on competition and productivity of the U.S. freight transportation industry

Pages in Study 46

Candidate for Degree of Master of Science

This study reviews the competition and productivity of the U.S. freight transportation industry for the past 41 years. This study investigated the trends of HHI market concentration index values and labor productivity values of rail and truck sectors and tried to find any relationships between the two values in the separate periods before and after the abolishment of the ICC. This study also investigated how the existence of a regulatory body impacted productivity of the freight transportation industry by using a Cobb Douglas production function on annual financial statement data in the U.S. stock exchange market. This study found that: while the truck sector became more competitive after the abolishment of the ICC, the rail sector became less competitive, both sectors had a strong positive correlation between HHI and labor productivity, and the ICC's abolishment resulted in positive changes of total factor productivity for the truck sector only.

Key words: Transportation, Deregulation, Competition, Productivity, Panel Data Regression

DEDICATION

To my wife, Heejean, to my children, Luke, and Lea, who have been so supportive through my whole study

ACKNOWLEDGEMENTS

I want to express my deep gratitude to my thesis committee (Dr. Li Zhang, Dr. Farshid Vahedifard, and Dr. Yingge Qu) for academic guidance through my graduate study of transportation engineering.

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CHAPTER I

INTRODUCTION

The Interstate Commerce Commission (ICC) was established in 1887 as a regulatory agency of the U.S. freight transport industry, including the rail sector and later, the truck sector. The starting point of economic deregulation of the U.S. transportation industry was considered to be the Airline Deregulation Act of 1978; the year 2018 was the 40th anniversary of the deregulation of the U.S. transportation industry (Fischer, 2018). In 1980, the U.S. freight transportation industry had been deregulated by the Stagger Rail Act of 1980 and the Motor Carrier Act of 1980. These laws significantly deregulated the U.S. freight transportation industry. The purpose of the economic deregulation in the transportation industry was to increase the transport market competition, which could lead to improvements in the industry's productivity by lowering costs and serving more consumers with lower rates. The culmination of economic deregulation in the U.S. freight transportation industry was the ICC Termination Act of 1995. At the end of 1995, the ICC was abolished: two transport industry sectors, the rail sector and the truck sector, have had different paths towards deregulation. While the truck sector has been fully deregulated, the rail sector was still controlled by the Surface Transportation Board (STB) even after the abolishment of the ICC. The reason for creation of the STB was to continue regulatory oversight of the freight rail market because historically the rail industry was considered as a natural monopoly due to the high building cost of rail networks (Layton, 2019). While the ICC used to take a comprehensive control of economics and services in the rail industry, the STB, a successor of the ICC, had reduced power to regulate the economic aspect of freight rail industry (Spychalski, 1997).

Winston (1998) generalized the deregulation in U.S. industries and their adjustments over the course of 20 years since the mid-1970s. He observed that after the deregulation, competition in the transportation industry had grown highly, operating costs of the truck and rail industry sectors had fallen significantly, and their profits had increased greatly. In addition, consumer welfare had increased. He concluded that an economic adjustment to deregulation would be shaped by increasing competition and long term efficiency. Holmes and Schmitz (2010) reviewed literature regarding the relationship between competition and productivity; they reviewed several industry cases, including rail transportation. They found that the increases in competition had led to increases in industry productivity.

The goal of this study is to find empirical evidence of the effect of deregulation on the competition and productivity levels in the U.S. freight transportation industry from 1980 to more recent years in the 21st century. Several previous studies in recent years (Holmes & Schmitz, 2010; Martland, 2013; Schmalensee & Wilson, 2016) were about deregulation of the rail industry; no studies have been done regarding the freight transportation industry, including both rail and truck industries simultaneously. In addition, previous studies compared the outputs of productivity in intervals of every 5th year or every 10th year, but this study uses a continuous data set of 41 years, analyzing each year of the publicly traded companies in the U.S. stock exchange markets. This study has the following research questions:

Q1: Is there any significant difference in industry competition level in the U.S. freight transportation industry after the ICC was abolished in 1995?

Q2: What relationship exists between the competition level and the industry's labor productivity? Is there any difference between two periods, one with the ICC and the other without the ICC?

Q3: Did the ICC have an impact on the productivity in the U.S. freight transportation industry since 1980, the year of starting economic deregulation, and after 1995, the year of ICC abolishment?

This paper is structured as follows. First, it presents a brief literature review and then presents the dataset used in this paper. In the following section, it presents the trends of market competition, the trends of labor productivity, and their correlation analysis. In the next section, it analyzes the ICC's effect on the productivity of freight transportation industry using a panel data regression model. Discussion and conclusion sections follow in the end.

CHAPTER II

BRIEF LITERATURE REVIEW

TR News, Transportation Research Board's magazine, had a special issue (May-June 2018), '40 Years of Transportation Deregulation'. Several articles within the special edition presented a historical view of deregulation and its effect on the U.S. rail and truck industries. John Fischer (2018) mentioned that the purpose of deregulation was to modify and modernize regulation, not to eliminate it; the economic freedom from the regulatory agency was to provide forces of innovation and efficiency to the U.S. transportation industries. Robert Gallamore (2018) compared the dynamic changes of traffic volume, revenue, price, and productivity in the U.S. railroad industry before and after the Stagger Act of 1980. He described how the railroad deregulation permitted an increase in traffic volume (ton-miles) and a decrease in average rail rates, which led to increased railroad productivity. He highlighted the advantage of deregulation in the technology improvements and operation innovation aspects of the railroad industry. Gallamore (2018) considered an intermodal freight service as a symbol of the freight industry's technological and operational innovation. He mentioned that long-term contracts between carrier-shipper partnerships allowed for intermodal container services of double-stack trains, which led to improved cash flow and re-investment towards technology improvement.

Martland (2012) compared the statistics of the U.S. railroad industry sector before and after deregulation; he observed that after the passage of the Stagger Act in 1980, the revenue per ton-miles had more than doubled while the railroad industry had reduced its track-miles, employees, and freight cars. Thus, the railroad industry had improved its productivity and profitability. He calculated the productivity by freight revenues and freight expenses for every 5th year, adjusted by a rail price index and a railroad cost recovery index, respectively. He found that productivity improvement was greater after 1980 and it began accelerating in 1990, going up to 9%, and declined to 4% in 2008. Schmalensee and Wilson (2016) argued that after the Staggers Act of 1980, railroad industries abandoned unprofitable lines and merged, differentiating pricing for the favored movement of goods and made substantial investments in track and equipment improvements. They compared various ratios of productivity in 10 year increments (starting from 1980), such as average railroad ton-miles, average network size, average length of haul, and ton-miles per train-hour. They found that all productivity ratios had an increasing trend. In summary, all four papers mentioned above (Martland, 2013; Schmalensee and Wilson, 2016; Fischer, 2018; Gallamore, 2018) found that there had been a positive effect of deregulation on productivity in the U.S. railroad industry.

The U.S. Bureau of Labor Statistics reviewed the deregulation effect on competition in the U.S. truck industry (Engel, 1998). This article examined factors affecting employment of the for-hire truck industry for the 30 years from 1970s. The article found that the transportation industry deregulation was one of the important factors, which led competition between transportation sectors and paid more attention to customer’s needs. In 1990s, customers wanted more quick-and-flexible delivery services, which made the transportation network adaptable to just-in-time delivery systems. Intermodal delivery systems, initiated by the Intermodal Surface Transportation Efficiency Act of 1991, provides a seamless flow of good from U.S. ports to destinations through railroads and highways. In the 1990s, 75% of freight was transported by trucks in the distribution chains. In summary, the strong competition in the U.S. truck industry was followed by the transportation deregulation and the increasing capital investment in the truck industry improved the quality of delivery services and reduced average variable costs.

There has been limited previous research on the truck industry sector in the 21st century. Edward Rastatter (2018) presented a history of deregulation in the U.S. truck industry. Since 1980, the number of carriers in the U.S. trucking industry had increased from 19,000 to 523,000, and most of them were small size trucking companies (less than 20 vehicles), which helped reduce logistics costs. Cassidy (2019) presented the market shares of the top 50 largest U.S. truck companies for 10 years from 2009 onwards. During the 10 years, the top 50's U.S. market shares in the for-hire truck market had risen steadily from 27% to 38%. For the last 20 years, the regional carriers have become multi-regional, national companies due to the acquisition of competitors. Thus, the market concentration rate in the top 50 companies in the 10 years from 2009 had risen higher in the early 21st century.

CHAPTER III

DATA

3.1 Data Items

This study uses the Compustat databases to obtain 41 years' worth of annual financial statements for U.S. publicly traded companies between 1980 and 2020. According to the North America Industry Classification Code (NAICS), which consisted of 6 digits, the transportation industry starts with 48 and the first three digits represent a sector (482 for the rail sector and 484 for the truck sector). The data set contains only companies listed in U.S. stock exchanges, such as the NYSE, AMEX, NASDAQ, and PHLX.

The numeric data items used in this study are Assets Total (AT), Number of Full-Time Workers (EMP), and Revenue Total (RT). The categorical data items are Fiscal Year (Year), NAICS, Security Exchange Code (SEC), and Ticker Symbol (TS). The TS represents the stock market symbol of an individual transportation company. In addition to the annual financial statement data items, the historic retail gas prices are added to the dataset. The average retail gas price of each year was obtained from the U.S. Bureau of Labor Statistics. Table 3.1 represents a list of data items in this study.

Table 3.1 Raw Data Items

Data Item	Name	Type	Source
AT	Assets Total	US $ (millions)	Compustat
EMP	Number of Full-Time Employee	Number (thousands)	
FY	Fiscal Year	Number (yyyy)	
NAICS	North America Industry Classification Code	Number (6 digits)	
RT	Revenue Total	US $ (millions)	
SEC	Security Exchange Code*	Number (2 digits)	
TS	Ticker Symbol	Text	
GAS	Average Retail Gas Price (All Types per Gallon)	US $	U.S. Bureau of Labor Statistics

* NYSE (11), AMX (12), NASDAQ (14), PHLX (18)

3.2 Data Processing

The total number of downloaded data records is 2,156. Among them, records with missing AT and RT were removed and zero values were also removed because of log transformations in later analysis. The remaining data set is 1,604 data records, in which there are 148 missing values of EMP. Because EMP is not a mandatory item in the annual financial statement, companies do not need to report their number of full-time employees to the U.S. Securities and Exchange Commission. To make up for the 148 empty EMP data, the k-nearest neighbor (kNN) imputation method was used. The kNN method predicts the value of missing variables from the average of the k value of the nearest neighbor found in the data set. In this study, 5 is used as a value of k.

3.3 Data Structure

The dataset in this study consists of four subsets by two categories: Sector and ICC. There are two transportation sectors (rail and truck), and two time periods; Period 1, 16 years with the ICC (1980 ~ 1995) and Period 2, 25 years without the ICC (1996 ~ 2020). The number of records in the rail sector is 635 and that in the truck sector is 969. The number of records in Period 1 is 743 and that in Period 2 is 861. (See Table 3.2)

Table 3.2 Four Subsets of Data

	Period 1: 1980 – 1995 (ICC =1)	Period 2: 1996 - 2019 (ICC=0)	Total
Rail (Sector=0)	381	254	635
Truck (Sector=1)	362	607	969
Total	743	861	1,604

There are 109 companies (39 in the rail sector; 70 in the truck sector) in the 41 year time period. If it is a completely balanced dataset, the number of records should be 4,469 (=109 companies * 41 years), but the total record is only 1,604. Thus, the dataset used in this study is unbalanced panel data. There are only five companies listed for all 41 years in the U.S. stock market, three in the rail sector (Burlington Northern Santa Fe, CSX Corp., and Kansas City Southern) and two in the truck sector (ARCBEST Corp. and Yellow Corp.).

3.4 Descriptive Statistics

Table 3.3 presents descriptive statistics of the three main variables, AT, EMP, and RT, and their log-transformed variables, ln(AT), ln(EMP), and ln(RT). Figure 3.1 shows histograms of those variables. While the histograms of the original three variables are extremely right skewed, the histograms of the log-transformed variables are generally close to normal distribution.

Table 3.3 Descriptive Statistics

	AT (millions)	EMP (thousands)	RT (millions)	ln(AT)	ln(EMP)	ln(RT)
n	1,604	1,604	1,604	1,604	1,604	1,604
Mean	4,819.96	12.44	2,427.04	20.47	8.55	20.43
Median	643.79	4.90	688.21	20.28	8.50	20.35
S.D.	12,007.68	14.79	4,025.61	1.94	1.51	1.68
Min	6.64	0.025	0.71	15.71	3.22	13.47
Max	88,660.00	75.00	23,988	25.21	11.23	23.90

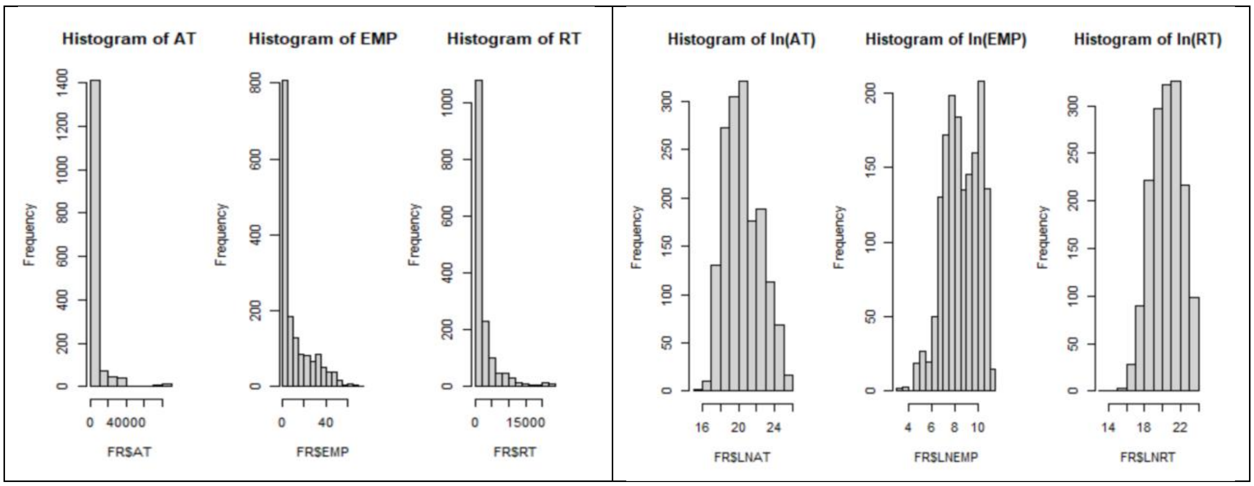

Figure 3.1 Histograms

Figure 3.2 presents boxplots of the log-transformed variables. Each boxplot chart consists of four columns of subsets by sectors (1: Rail, 0: Truck) and periods (1: Period 1, 0: Period 2); (0, 0) = (Rail, Period 2), (1, 0) = (Truck, Period 2), (0, 1) = (Rail, Period 1), and (1,1) = (Truck, Period 1). Comparing the two periods, each sector has higher values of three quartiles (Q1, Q2, Q3) in Period 2 than in Period 1.

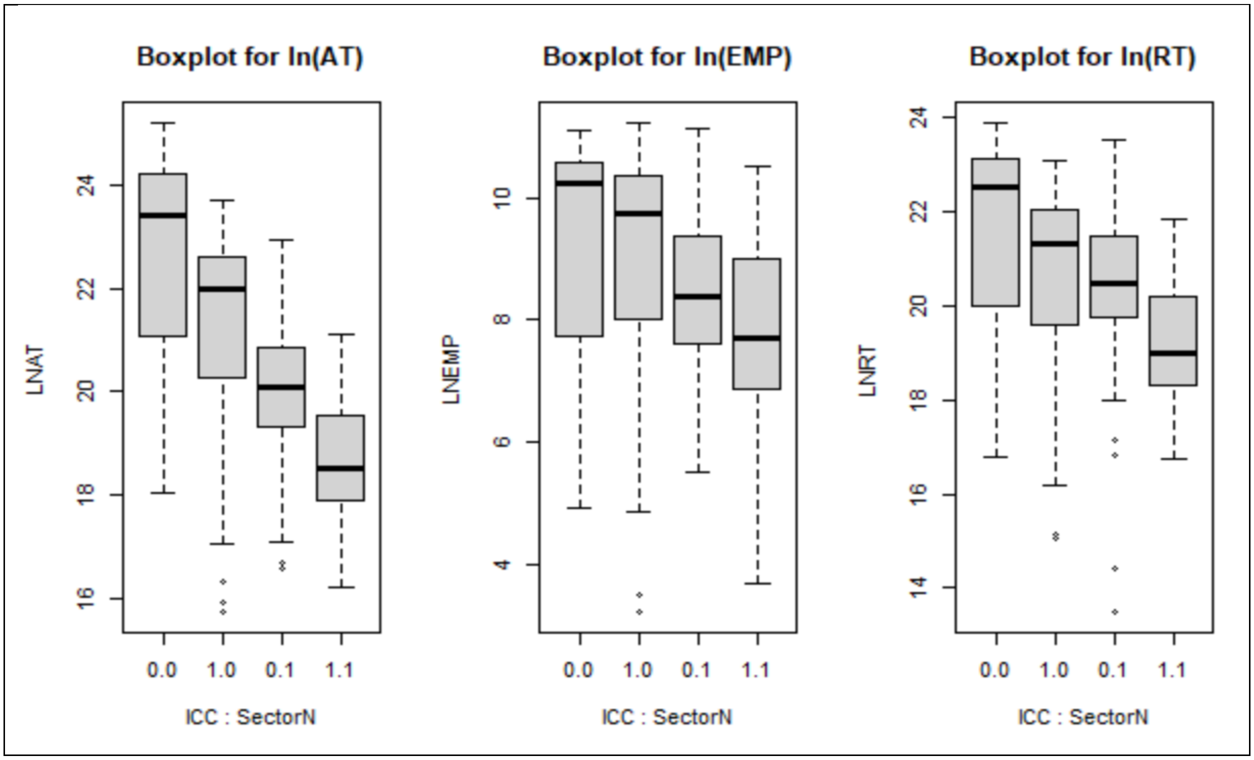

Figure 3.2 Box-Plot

CHAPTER IV

MARKET COMPETITION AND LABOR PRODUCTIVITY

4.1 Market Concentration Index

The Herfindahl-Hirschman Index (HHI) is a well-known measure of the market concentration index and it is the sum of the squares of each company's percentage of industry sales (Shin and Eksioglu, 2015). Because the HHI gives greater weight to the larger market percentage, an industry with a large number of small companies, i.e. a competitive market, has a low HHI index, while an industry with a small number of large companies, i.e., a concentrated market, has a high HHI index. According to Horizontal Merger Guidelines (1997, U.S.DOJ and FTC), the U.S. Department of Justice uses the HHI index when it evaluates a potential merger and acquisition issue. It divides the spectrum of market concentration into three categories of market competition: (1) competitive (HHI <=1,500), (2) moderately concentrated (1,500 < HHI <= 2,500), and (3) highly concentrated (HHI > 2,500) (Marshall, Bruce, and MacGill, 2021). This study uses the HHI index as a proxy of the market competition level. For example, there are six rail companies in the rail sector in 2020. A market share of each company is calculated as a percent of the revenue out of the sum of all the companies' revenue, i.e. Market Sharei = (RTi / ∑RTi)*100. The HHI is calculated by summing the squares of market share percentage of each individual company, i.e., HHI = Σ (Market Sharei)^2, and the HHI value of year 2020 in the rail sector is 2,059.69 (see Table 4.1).

Table 4.1 HHI Calculation Example

Year	Company Name	RT	Market Share	(Market Share)^2
2020	Burlington Northern Santa Fe	20,869.0	24.97%	623.35
2020	BNSF Railway Co	20,180.0	24.14%	582.87
2020	Union Pacific Corp	19,533.0	23.37%	546.09
2020	CSX Corp	10,583.0	12.66%	160.30
2020	Norfolk Southern Corp	9,789.0	11.71%	137.16
2020	Kansas City Southern	2,632.6	3.15%	9.92
Total		**83,586.6**	**100.00%**	**2,059.69**

Figure 4.1 presents a trend of the number of companies and HHI values in each sector. While the number of companies in the both sectors had an upward trend between 1980 and 1995, it had a downward trend between 1996 and 2020. By mergers and acquisitions in 1995 – 1998, the number of rail companies listed in the U.S. stock market was less than 15 in 1999. Since the 2003 merger between the two largest truck companies, Yellow Corporation and Roadway Corporation, the number of truck companies had decreased from 2003 through 2007; after that, the number of truck companies listed in the U.S. stock market have been stable at a total of 20 or a little over. This is the same phenomenon that was observed by Cassidy (2019), that there have been active mergers and acquisitions for the last 20 years among the large truck companies and their concentration had been increasing.

For the HHI trends, while the truck sector stayed at a competitive market (HHI <= 1500) except for the early 1980s, the rail sector had experienced a stepwise increase of its HHI level. The rail sector had stayed at a competitive market (HHI <= 1500) in Period 1. For 9 years after 1995, it had been on the borderline (HHI = 1500) between a competitive market and a moderate concentrated market. Since 2005, the HHI value of the rail industry has stayed at around 2,000 at a moderate concentrated market (1,500 < HHI <= 2,500).

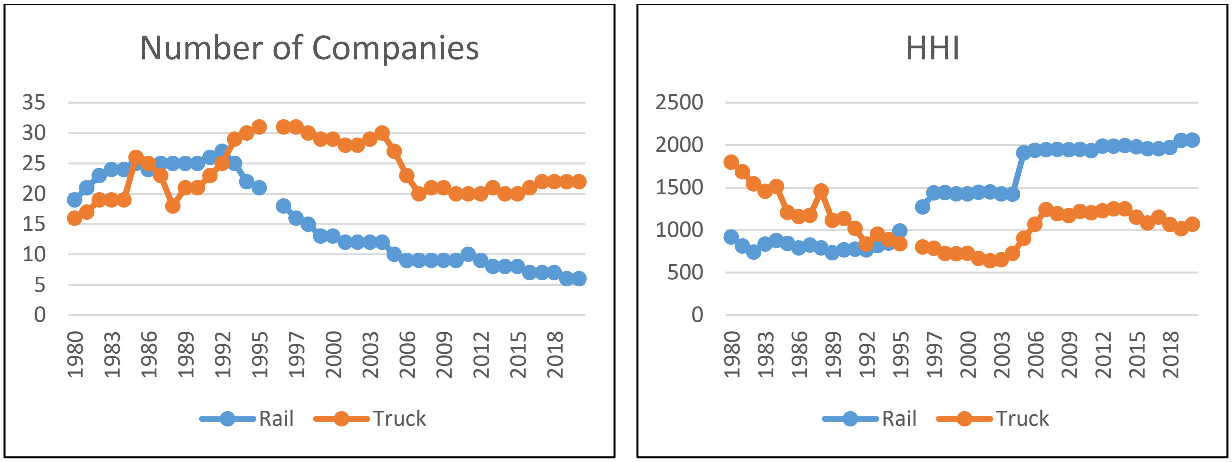

Figure 4.1 Number of Companies and HHI

4.2 T-test for HHIs

As mentioned earlier, the HHI data items are grouped by two periods: Period 1 (1980 ~ 1995) and Period 2 (1996 ~ 2020). Two-sample t-tests determines whether the mean values of the HHI in the two periods are equal. The t-tests are assumed as unequal variances. Table 4.2 presents the output of the t-tests of the rail and truck sectors. In both sectors, the null hypotheses (Ho), the equal mean values of the two periods, are not accepted at a significance level of 1%. Thus, the mean HHI values in two periods are different. While the mean HHI of the rail sector in Period 2 is higher ($\mu_{R1} < \mu_{R2}$), the mean HHI of the truck sector in Period 1 is higher ($\mu_{T1} > \mu_{T2}$). Therefore, while the level of competition in the trucking sector was improved in Period 2, the level of competition in the rail sector was worse from the competition point of view.

Table 4.2 Results of t-tests

sector	Rail		Truck	
period	**Period 1**	**Period 2**	**Period 1**	**Period 2**
Ho	$\mu_{R1} = \mu_{R2}$		$\mu_{T1} = \mu_{T2}$	
n	16	25	16	25
mean	821.40	1,772.05	1340.2	984.7
variance	4,386.65	75,643.82	106,213.5	54,909.4
df	28		25	
t Statistics	-16.55		2.80	
p-value (one-tail)	0.0000		0.0049	
p-value (two-tail)	0.0000		0.0098	

4.3 Labor Productivity

Labor productivity is a ratio between output total, which is the amount of goods and services produced, and amount of labor used for producing those goods and services. The U.S. Bureau of Labor Statistics publishes labor productivity with the number of hours worked as an input factor. In this paper, RT and EMP, as proxy values for output total and labor factor, are used to calculate labor productivity per full-time employee. Figure 4.2 presents a trend of labor productivity in both sectors. Since 1980, the labor productivity has continuously been increasing and the labor productivity for the rail sector is always higher than that for the truck sector. The labor productivity gap between two sectors has been getting wider continuously.

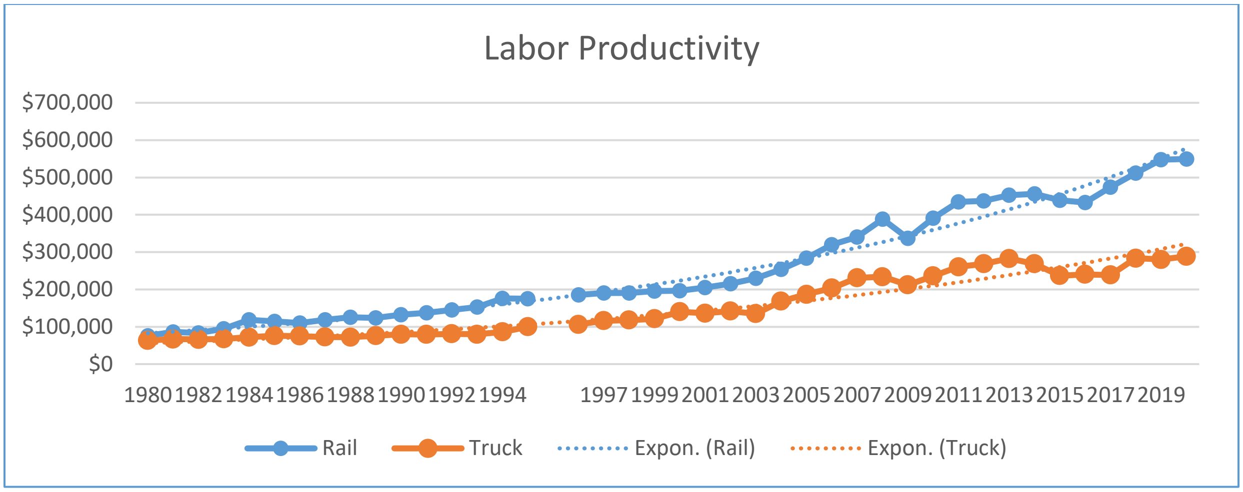

Figure 4.2 Labor Productivity with Exponential Trend Lines

4.4 Correlation Analysis

Backus (2019) researched industry-level correlations between productivity and competition. He found that more competitive markets induced companies in the markets to find the more efficient production ways, which led to enhanced productivity, i.e., there is a positive correlation between competition and productivity. In this study, a correlation analysis with HHI and labor productivity was made. A negative correlation between HHI and labor productivity means that there is a positive correlation between labor productivity and the market competition level. While there is a strong negative correlation (-0.8614) in Period 1 of the truck sector, there is a strong positive correlation (0.9015 & 0.8642) in Period 2 of the both sectors. Therefore, in only Period 1, the competition level and labor productivity in the truck sector goes to the same direction, i.e., the more competitive it is, the higher the productivity becomes. In Period 2, both sectors show that the less competitive it is, the higher the productivity becomes, indicating a different result from Backus's study. Figure 4.3 and Figure 4.4 present trend lines of labor productivity and HHI of both sectors.

Table 4.3 Results of Correlation Analysis between HHI and Labor Productivity

	Period 1 (1980 ~ 1995)	Period 2 (1996~2020)
Rail	0.2114	0.9015
Truck	-0.8614	0.8642

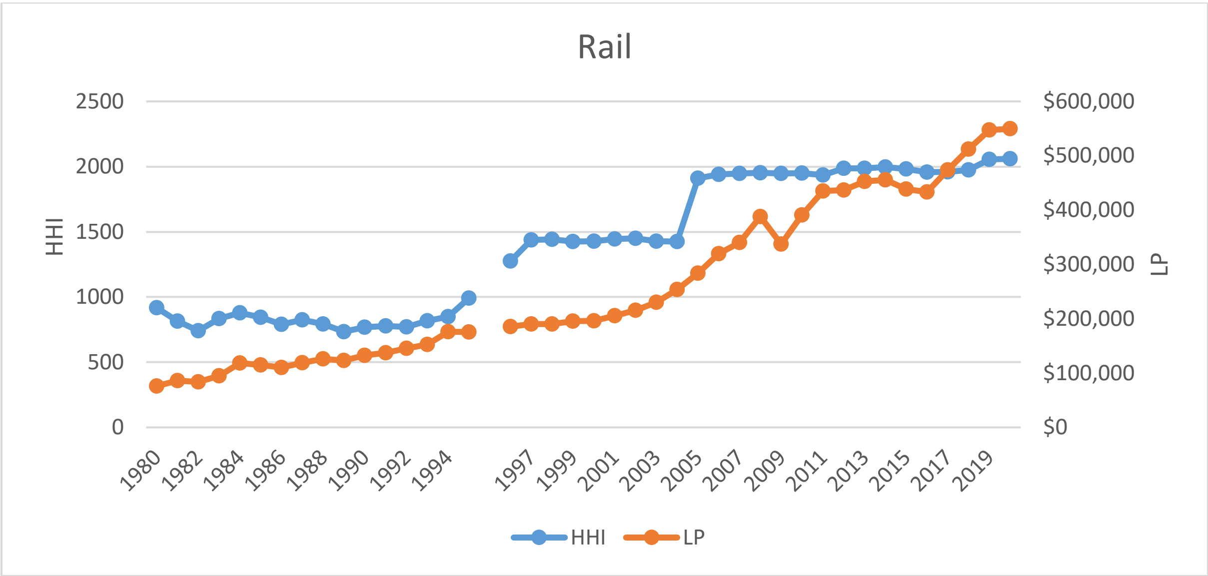

Figure 4.3 Comparison between HHI and Labor Productivity (LP) – Rail Sector

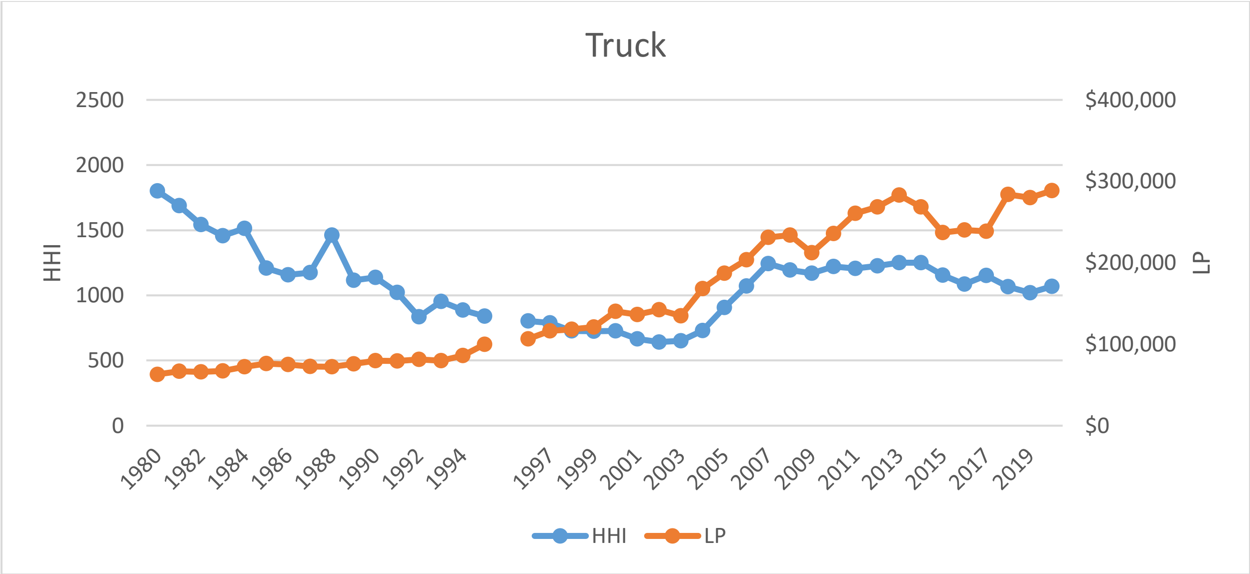

Figure 4.4 Comparison between HHI and Labor Productivity (LP) – Truck Sector

CHAPTER V

REGRESSION ANALYSIS

5.1 Cobb-Douglas Production Function

The Cobb-Douglas production function is used to represent the relationship between an output and two inputs, capital (K) and labor (L) (Shin and Eksioglu, 2015). It was developed for statistical evidence with U.S manufacturing industry data by Cobb and Douglas in 1928 (Bao Hong, 2008). The assumptions in the Cobb-Douglas production function are: that capital and labor are the two inputs for determining a level of production, and that the marginal productivity of capital/labor is proportional to the amount of production per unit of capital/labor (Michael, 2019). Equation (1) is the production function used by Cobb and Douglas:

$$P(L,K) = AK^{\alpha}L^{\beta} \tag{5.1}$$

where P = total production, L = labor input, K = capital input, A = total factor productivity, α = output elasticity of labor, and β = output elasticity of capital.

Total production refers to “the monetary value of all goods and services produced in a year” (Bao Hong, 2008). The number of full-time employees and fixed assets are typically used for capital and labor inputs (Shin and Eksioglu, 2014). Total factor productivity (TFP) is “the portion of output not explained by the amount of inputs used in production” (Comin, 2006). TFP is assumed to be a constant that is independent of both labor and capital but TFP could vary due to technology innovations or changes in industry policy. Intermodal freight transportation is a good example of TFP change due to technology innovation, while deregulation is an example of TFP change due to industry policy. In the transportation industry, the two largest operating expenses are fuel and employee salary (Coyle, Novack, and Gibson, 2015). In addition to capital and labor, fuel (F) is another important input in the transportation operation.

The equation (2) is a modified Cobb-Douglas production function used in this study:

$$P(L,K,F) = AK^{\alpha}L^{\beta}F^{\gamma} \tag{5.2}$$

where F = Fuel and γ = output elasticity of fuel

Applying the log transformation to the equation (2), a linear model is generated:

$$lnP(L,K,F) = ln(A) + \alpha*ln(K) + \beta*ln(L) + \gamma*ln(F)+\varepsilon_{ij} \tag{5.3}$$

In equation (3), the output elasticity of each input (α, β, γ) becomes a coefficient of the log-transformed variables. The outputs of the transportation industry are services with movement of people and products and the outputs should be measured in dollar units (Ingene & Lusch, 1999). According to King & Park (2004), while the U.S. Census Bureau uses gross income as a measure of output, the U.S. Bureaus of Labor Statistics uses sales/revenue as an output. Sales/revenue is frequently used for the total output in service industry analysis (Shin and Eksioglu, 2015). In this study, sales/revenue, i.e. RT, is used for the output in the modified Cobb-Douglas production function. Because of the absence of gas consumption information, we used an average retail gas price assuming to influence the same effect on both transportation sectors. In addition, a binary dummy variable, ICC, is added to find an effect of ICC to productivity of each sector. The following equation will be used for basic linear regression analysis:

$$ln(RT_{ij})=ln(A)+ \alpha * ln(AT_{ij}) + \beta * ln(EMP_{ij}) +\gamma *ln(GAS_i)+ \delta *ICC +\varepsilon_{ij} \tag{5.4}$$

where i = fiscal year 1980 ~ 2020, j = Ticker Symbol, RT =Revenue Total, AT = Asset Total, EMP = Number of Full-Time Employee, GAS= Average Retail Gas Price, , ICC =1 if ICC exists, otherwise 0

5.2 Pooled Regression Model

This study uses both cross-sectional and time-series panel data, which has 109 companies (39 for the rail sector and 70 for the truck sector) and 41 years. The pooled regression model ignores the time series dimension and it considers the dataset as cross-sectional data. Table 5.1 presents the output of the pooled regression model with the equation (4). While the p-values of all coefficients are 0.000 in the rail sector, the p-values of ln(GAS) and ICC are not significant at the 5% significance level in the truck sector. The pooled regression models need to be tested for multicollinearity, residual analysis, and homeoskedasticity. Table 5.2 presents the results of the Breusch-Pagen (BP) test and values of VIF (Variance Inflation Factor). In the BP test of both sectors, the null hypothesis of constant variance was rejected, indicating that both sectors have a heteroscedasticity issue. While values of VIF in the truck sector are less than 10, indicating no multicollinearity, VIF values of ln(AT) and ln(EMP) in the rail sector are greater than 10, indicating multicollinearity. Even if the Cobb-Douglas production function is the best production function used in production analysis, one of the issues is multicollinearity (Enaami, Ghani, and

Mohamed, 2011). Thus, one of variables with the high correlation should be dropped. However, because the main focus in the analysis is to compare the TFP of the two periods, a period with ICC and a period without ICC, the equation (4) will be used in both sectors in the further analysis.

Table 5.1 Results from the Pooled Regression Model

Sector	Intercept (p-value)	α (p-value)	β (p-value)	γ (p-value)	δ (p-value)	R^2
Rail	2.230 (0.000)	0.725 (0.000)	0.312 (0.000)	0.155 (0.000)	0.122 (0.000)	0.988
Truck	1.057 (0.004)	0.946 (0.000)	0.054 (0.025)	0.081 (0.131)*	0.028 (0.539)*	0.883

* > 0.05

Table 5.2 Test Statistics and Results

Test	Rail	Truck
VIF for Multicollinearity	ln(AT) 14.15 ln(EMP) 12.37 ln(GAS) 2.47 ICC 2.72 Result: Multicollinearity*	ln(AT) 5.05 ln(EMP) 3.64 ln(GAS) 2.20 ICC 2.10 Result: No Multicollinearity
Breusch-Pagan test for Homoscedasticity (Ho: Homoscedasticity)	$\chi^2 = 61.46$ p-value = 0.0000 Result: Heteroskedasticity*	$\chi^2 = 9.12$ p-value = 0.0025 Result: Heteroskedasticity*

* OLS violation

5.3 Residual Analysis

The residual plots in Figure 5.1 are scatter plots of fitted values and residuals. Both residual plots (rail and truck) show data randomly dispersed around a horizontal zero line except for two outliers (residual = -5.65 &-5.51) in the truck sector. Thus, there are no specific patterns in the residual plots and the linear model is a good fit for both sectors. These two outliers in the truck sector are removed and the total number of observations in the truck sector is 967 in the following panel regression analysis.

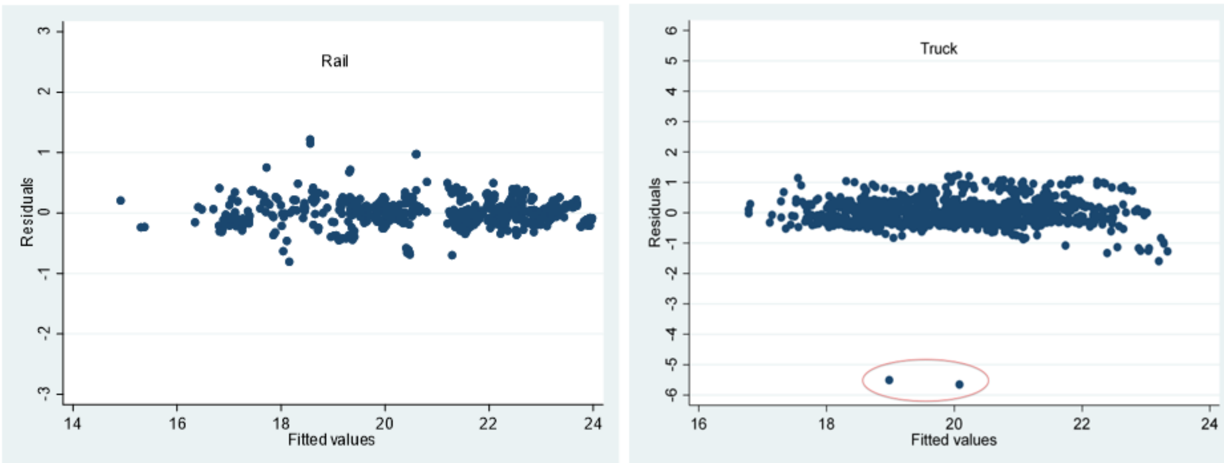

Figure 5.1 Residual Plots

Table 5.3 presents the summary statistics of residuals of each sector. The mean value of residuals of each sector is close to zero. Table 5.4 presents the covariance values between the residuals and the independent variables of each sector. All covariance values are also close to zero, indicating that there is no endogenous issue.

Table 5.3 Summary of Residuals

Sector	Obs.	Mean	S.D.	Min	Max
Rail	635	1.83e-13	0.2126	-0.8057	1.2185
Truck	969	-2.92e-10	0.4682	-5.6525	1.2432

Table 5.4 Covariance with Residuals

Sector	Obs.	LNAT	LNEMP	LNGAS	ICC
Rail	635	5.3e-11	3.6e-10	1.5e-10	-6.3e-11
Truck	969	-3.2e-10	1.5e-10	-7.3e-11	5.0e-11

5.4 Panel Data Regression Model

Because both sectors have a heteroscedasticity issue in the pooled regression model and because the rail sector has a multicollinearity issue, a panel data regression is introduced. The panel data in this model consists of a panel ID variable, a variable that identifies each transportation company, and a time variable. Because the panel ID variable is a variable measured at multiple points in time, the panel data is also called cross-sectional time series data (Bartels, 2009).

The most frequently used panel data regression models are fixed effect models and random effect models (Shin and Eksioglu, 2014). While the fixed effect model assumes that dummies are considered part of the intercept term and the same slopes and constant variance across individual companies, the random effects model assumes that dummies act as an error term and the difference among individual groups or time periods lies in their variance of the error term (Greene, 2012). Equation (4) is used for the panel data regression with TS as a panel ID variable and FY as a time variable.

Table 5.5 presents the outputs of both panel regression models. P-values of all coefficients and model p-values are 0.000, indicating that the models are well fitted and all coefficient are acceptable at a significance level of 1%. The Hausman test can be used to differentiate between the fixed effect model and the random effect model. The null hypothesis (Ho) is “a random effect model is appropriate” while the alternative hypothesis (Ha) is “a fixed effect model is appropriate” (Ishaq, Amin, and Khan, 2018). The result of the Hausman test of both sectors is that the fixed effect model is more appropriate at a significant level of 1%. Additional tests to do before we accept the fixed effect model is the Woodridge test for autocorrelation in panel data. Table 5.6 presents that both datasets have an issue of autocorrelation with a significance level of 1%. Table 5.7 presents the results of the fixed effect regression model with a robust standard error, which is a remedy for panel data with heteroscedastic, autocorrelated error structure (Greene, 2012). The only differences between the two fixed models (Table 5.5 and Table 5.7) are the p-values of the coefficients. In Table 5.7, the p-values of ln(GAS) and ICC in the rail sector and the p-value of ln(EMP) in the truck sector are over 0.05, indicating that those coefficients are not statistically significant at a significance level of 5%. A likelihood ratio (LR) test is used for panel data homoscedasticity. The LR test is a Chi-square test between a model of homoscedastic assumption and a model of heteroscedastic assumption. Both sectors are homoscedastic. However, both sectors' panel data have still multicollinearity issues because their values of VIF for ln(AT) and ln(EMP), are greater than 10.

Table 5.5 Panel Regression Results

Sector	Rail (n=635)		Truck (n=967)	
Model	Fixed Effect	Random Effect	Fixed Effect	Random Effect
Intercept	3.761 (0.000)	3.036 (0.000)	4.674 (0.000)	4.523 (0.000)
ln(AT)	0.712 (0.000)	0.727 (0.000)	0.762 (0.000)	0.767 (0.000)
ln(EMP)	0.178 (0.000)	0.220 (0.000)	0.049 (0.000)	0.052 (0.000)
ln(GAS)	0.111 (0.000)	0.108 (0.000)	0.255 (0.000)	0.248 (0.000)
ICC	0.089 (0.000)	0.107 (0.000)	-0.166 (0.000)	-0.155 (0.000)
R^2	0.986	0.987	0.906	0.907
Model Fit	F = 1,810.94 p = 0.000	F = 9,880.02 p = 0.000	F = 5,263.34 p=0.000	F = 21,494.47 p = 0.000

Table 5.6 Test Statistics and Results for Panel Regression Models

Test	Rail (n=635)	Truck (n=967)
Hausman Test (with sigmamore option) (Ho: Random Effect Model)	χ^2 = 52.10 P= 0.000 Result: Fixed Effect	χ^2 = 15.65 P = 0.0035 Result: Fixed Effect
Wooldridge test for Autocorrelation (Ho: No autocorrelation)	F = 26.30 p-value = 0.000 Result: Autocorrelation*	F = 76.17 p-value = 0.000 Result: Autocorrelation*
Likelihood Ratio Test for Homoscedasticity (Ho: Heteroscedasticity)	LR χ^2 = 313.44 P-value = 0.000 Result: Homoscedasticity	LR χ^2 = 933.34 P-value = 0.000 Result: Homoscedasticity
VIF for Multicollinearity (with uncentered option)	ln(AT) 92.36 ln(EMP) 77.07 ln(GAS) 4.86 ICC 4.45 Result: Multicollinearity*	ln(AT) 113.49 ln(EMP) 102.75 ln(GAS) 5.13 ICC 2.85 Result: Multicollinearity*

* OLS violation

Table 5.7 Fixed Effect Panel Regression Model with Robust Std. Error

	Rail (n=635)		Truck (n=967)	
	Coefficient	p-value	Coefficient	p-value
Intercept	3.761	0.003	4.694	0.000
ln(AT)	0.712	0.000	0.762	0.000
ln(EMP)	0.178	0.004	0.049	0.133*
ln(GAS)	0.110	0.085*	0.255	0.000
ICC	0.089	0.133*	-0.166	0.000
R^2	0.986		0.959	
Model Fit	F= 144.22, p= 0.000		F=342.76, p = 0.000	

* > 0.05

5.5 Panel Data Generalized Least Square Regression

Hoechle (2007) suggested two models for use in overcoming heteroskedastic, cross-sectional correlated, and autocorrelated panel data: (1) the Feasible Generalized Least Square (FGLS) when $N < T$ and (2) the Panel Corrected Standard Error (PCSE) when $N > T$, T = time dimension and N = cross-sectional dimension. The panel data set in this study have T = 41 years and N = 39 companies (rail sector) or 70 companies (truck sector). However, because of the unbalanced characteristics of the dataset used in this study, the time periods are not all common and the covariance matrix cannot be estimated. Therefore, the PCSE model is not viable for the panel dataset of this study and the FGLS model, which is good when the covariance structure is unknown, is used for both sectors. The following is the output from the FGLS regression model with a common first-order autocorrelation option. However, the FGLS regression models cannot also resolve the multicollinearity problem because of the unbalanced panel data structure.

Table 5.8 Feasible General Least Square Panel Regression Model

	Rail (n=635)		Truck (n=967)	
	Coefficient	p-value	Coefficient	p-value
Intercept	1.809	0.000	5.332	0.000
ln(AT)	0.772	0.000	0.697	0.000
ln(EMP)	0.239	0.000	0.113	0.000
ln(GAS)	0.222	0.000	0.299	0.000
ICC	0.171	0.000	-0.046	0.070*
Model Fit	Wald χ^2 = 13,076.90, p= 0.000		Wald χ^2 = 3,899.56, p = 0.000	

* > 0.05

5.6 Industry/Sector Level Analysis

The main focus of the regression analysis in this study is to find any differences in the productivity of the two sectors between Period 1 (ICC=1) and Period 2 (ICC=0). The dataset structure used in the previous sections are based on annual values of RT, AT, and EMP of individual freight transportation companies. Because of the limitation of analysis with unbalanced datasets, the authors made a new dataset structure based on annual values of RT, AT, and EMP of an industry-sector level. In each of the 41 fiscal years, the data items such as RT, AT, and EMP are averaged and converted into log-transformed data. The dimensions of each data set is a single dimension of 41 years of observations. The following table presents the descriptive statistics of log-transformed of averaged RT, AT, and EMP items of each sector.

Table 5.9 Descriptive Statistics of Industry/Sector Data Set

	ln(AT)	ln (EMP)	ln (RT)	ln (AT)	ln (EMP)	ln (RT)
Sector	Rail			Truck		
n	41	41	41	41	41	41
Mean	23.14	9.97	22.27	20.08	8.85	20.67
Median	23.17	9.99	22.24	19.97	8.85	20.66
S.D.	0.94	0.18	0.70	0.80	0.26	0.78
Min	21.73	9.64	21.29	19.08	8.40	19.64
Max	24.72	10.26	23.48	21.66	9.33	21.90

Equation (5) is the same as the equation (4) except for no j index, because the data set is summarized by the time variable (FY). The equation (5) is used for the industry-sector level regression analysis.

$$ln(RT_i)=ln(A)+ \alpha * ln(AT_i) + \beta * ln(EMP_i) +\gamma * ln(GAS_i)+ \delta * ICC +\varepsilon_i \qquad (5.5)$$

where i = fiscal year 1980 ~ 2020, RT =Revenue Total, AT = Asset Total, EMP = Number of Full-Time Employee, GAS= Average Retail Gas Price, , ICC (1 if ICC exists, otherwise 0)

Table 5.10 and Table 5.11 present the results from the pooled regression model using the industry/sector dataset and its test statistics. While the p-values of coefficients in the rail sector are zero except for the coefficient of ICC (0.012), the p-value of coefficients in the truck sector are also zero except for the ln(EMP), which cannot be accepted at a 5% significance level. While there is no violation of OLS assumptions in the rail sector, the truck sector data has violations regrading multicollinearity and autocorrelation. Therefore, the pooled regression model cannot be applied to the truck sector data set.

Table 5.10 Results from the Pooled Regression Model

Sector	Intercept (p-value)	α (p-value)	β (p-value)	γ (p-value)	δ (p-value)	R^2
Rail	4.907 (0.000)	0.651 (0.000)	0.214 (0.001)	0.251 (0.000)	0.086 (0.012)*	0.995
Truck	6.409 (0.000)	0.635 (0.000)	0.157 (0.310)**	0.375 (0.000)	-0.212 (0.000)	0.994

* > 0.01, ** > 0.05

Table 5.11 Test Statistics and Results

Test	Rail	Truck
VIF for Multicollinearity	ln(AT) 7.67 ln(EMP) 3.98 ln(GAS) 3.87 ICC 1.66 Result: No Multicollinearity	ln(AT) 25.05 ln(EMP) 14.93 ln(GAS) 4.34 ICC 3.13 Result: Multicollinearity*
Breushc-Pagan test for Heteroskedasticity (Ho: Homoskedasticity)	χ^2= 0.63 p-value = 0.4282 Result: Homoskedasticity	χ^2 = 0.10 p-value = 0.7555 Result: Homoskedasticity
Durbin-watson test for autocorrelation (Ho: No autocorrelation)	DW d (5, 41) = 1.431 d_l(5,40, 0.01) = 1.047 d_u(5,40, 0.01) = 1.583 Result: No autocorrelation	DW d (5, 41) = 0.9612 d_l(5,40, 0.01) = 1.047 d_u(5,40, 0.01) = 1.583 Result: Autocorrelation*

* OLS violation

The residual plots in Figure 5.2 are scatter plots of the fitted values and residuals from the above pooled regression model. Both residual plots show data randomly dispersed around a horizontal zero line. Thus, there are no specific patterns and the linear model is a good fit for both sectors. Table 5.12 presents the summary statistics of residuals for the industry-sector dataset. The mean value of residuals of each sector is close to zero and the standard deviation is much smaller than that of the item level data set because the industry-sector data set is a summarized dataset. Table 5.13 presents covariance values between residuals and independent variables of the industry-sector data set. All covariance values are also close to zero.

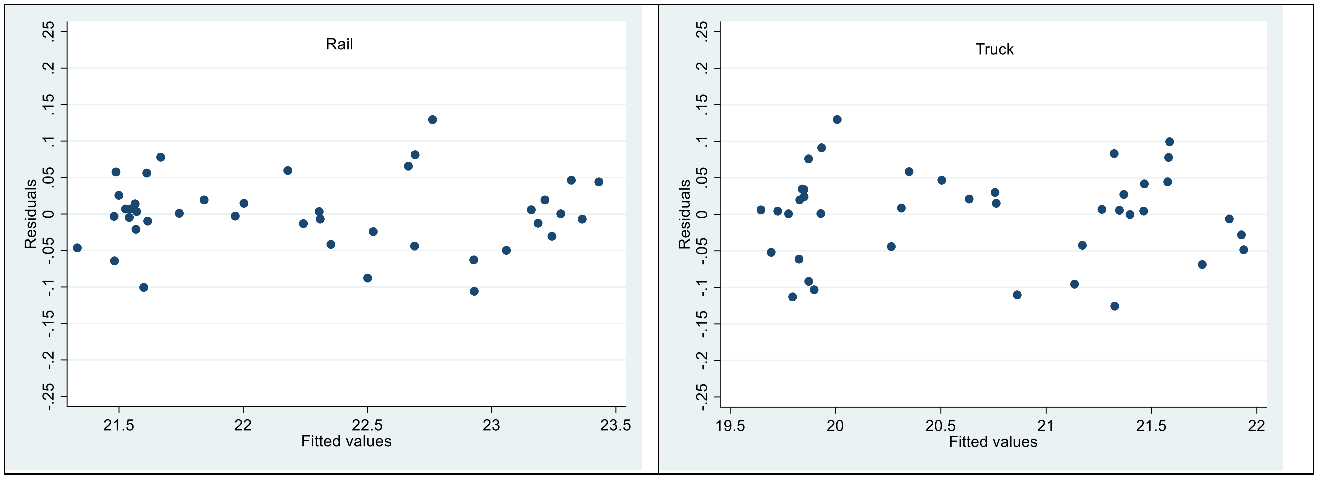

Figure 5.2 Residual Plots for Industry/Sector Data Set

Table 5.12 Summary of Residuals for Industry/Sector Data Set

Sector	Obs.	Mean	S.D.	Min	Max
Rail	41	-4.34e-10	0.0494	-0.1060	0.1294
Truck	41	-1.85e-10	0.0624	-0.1257	0.1298

Table 5.13 Covariance with Residuals for Industry/Sector Data Set

Sector	Obs.	ln(AT)	ln(EMP)	ln(GAS)	ICC
Rail	41	1.2e-110	-3.3e-11	-6.4e-11	-3.9e-11
Truck	41	5.8e-11	2.2e-11	4.4e-11	-1.3e-11

Because the industry-sector data set is a time-series data set, the FGLS regression model is used to overcome multicollinearity and autocorrection problems assuming that there is only one panel ID item, i.e., sector. The dimension of the industry-sector data set is 1*41, N= 1 (sector) and T=41 (year). Table 5.14 is the output from the FGLS regression model. The model fit is good for both sectors with a p-value of 0.000 in Wald F-statistics. Because there is no violation of OLS assumptions for the trail sector, the coefficients and their p-values in the rail sector are identical from the result of the pooled regression model. The FGLS regression model with a correction of multicollinearity and autocorrelation is applied to the truck sector. All coefficients are accepted at a significance level of 1% except for the coefficient of the ln(EMP) variable in the truck sector dataset, which is accepted at a significance level of 5%.

Table 5.14 Feasible General Least Square Panel Regression Model for Industry/Sector Data Set

	Rail (n=41)		Truck (n=41)	
	Coefficient	p-value	Coefficient	p-value
Intercept	4.907	0.000	5.442	0.000
ln(AT)	0.651	0.000	0.617	0.000
ln(EMP)	0.214	0.000	0.304	0.024*
ln(GAS)	0.251	0.000	0.368	0.000
ICC	0.086	0.005	-0.161	0.000
Model Fit	Wald χ^2 = 8,063.59, p= 0.000		Wald χ^2 = 2,702.39, p = 0.000	

* > 0.01

CHAPTER VI

DISCUSSION

In this study, the authors are interested in the values of TFP for each period and each sector, which is the sum of the intercept and a coefficient of dummy variable, ICC. Table 6.1 presents the intercepts and coefficients of ICC from Table 5.14, and add both values together. Because the equation (5) is transformed with log functions, the 'ln(A) + Coefficient of ICC' values are reversed with exponential functions to get the TFP values. Comparing the TFP values between Period 1 (ICC=1) and Period 2 (ICC=0), shows that in the rail sector, the TFP value of Period 2 is lower than that of Period 1, while in the truck sector, the TFP value of Period 2 is higher than the Period 1. Thus, while TFP of the rail sector decreased by 8.24% from Period 1 to Period 2, TFP of the truck sector increased by 17.47%. Therefore, when comparing the TFCs between the two periods, there is an increasing TFC in the truck sector and a decreasing TFC in the rail sector.

Table 6.1 Total Factor Productivity

Sector	Rail		Truck	
period	Period 1 (ICC=1)	Period 2 (ICC=0)	Period 1 (ICC=1)	Period 2 (ICC=0)
(a) ln(A)	4.907	4.907	5.442	5.442
(b) Values from ICC variable	0.086	0.000	-0.161	0.000
(c) (a) + (b)	4.993	4.907	5.281	5.442
(d) TFP = exp^(c)	147.4	135.2	196.6	230.9
(e) TFP Change (%)	-8.24%		17.47%	

As we mentioned earlier, technology innovations and industry policy can explain the improvement of TFP values. In the U.S. freight transportation industry, intermodal transportation and deregulation are good examples of technology innovations and industry policy (Gallamore, 2018).

Thomas Gale Moore (2007) mentioned that as a result of the Motor Carrier Act of 1980 and the Staggers Rail Act of 1980, the rail and truck industry sectors developed trailer-on-flatcars (TOFC) and container-on-flatcars (COFC), which enabled intermodal transport services. Both sectors had increased their productivity during the 1990s, but it was not easy to know which factor, deregulation or technological improvements, was the main factor for that increase.

Martland (2013), Schmalensee and Wilson (2016), and Gallamore (2018) observed that the productivity increases in the U.S. railroad industry in terms of traffic-related metric and intermodal freight services have been symbols of technological and operational innovation. According to the report from the Association of American Railroads (2020), the U.S. rail intermodal volume has increased since the 1990s; in 2020, the intermodal service accounted for 25% of revenue for Class-I U.S. railroads. The intermodal rail service provides a competitive price to customers and it is the top commodity category transported by U.S. Class-I railroads. However, in the analysis of this study, the rail sector's TFP has become lower after the abolishment of the ICC. This phenomenon can be explained by the rail sector industry's characteristics: low market competition and partial deregulation after the abolishment of the ICC. It is because traditionally the rail industry market structure was a duopoly by the two rail network providers on each side of Mississippi river, BNSF and Union Pacific in the west and CXS and Norfork Southern in the east.

The Surface Transportation Board published a report (2009) about the competition in the U.S. rail industry, which was initiated by the recommendation from the U.S. Government Accountability Office in order to check the possible market power abuse by the U.S. railroad carriers. The STB report used the ratio about price over marginal cost as a measure of exercising market power. The STB found that in the years from 1987 to 2006, there was no evidence for Class I railroad industry to earn above normal profit, and in 2007 and 2008, the railroad rate increase was a result of declining productivity growth and increased cost. This result is similar as the HHI trends in the rail industry in the Figure 4.3; in 2005, the HHI values of the rail sector jumped up from a competitive market to lightly concentrated market.

On the other hand, from the analysis of TFP values, the fully deregulated truck sector's TFP was increased after the abolishment of the ICC. In summary, while the abolishment of the ICC had a positive effect on productivity growth in the truck industry sector, it had a negative effect in the rail industry sector.

Winston (1998) evaluated the deregulation effect on the competition and productivity of 20th century U.S. freight transportation. Schmalensee and Wilson (2016) did the same analysis for the rail sector with an extension into the first decade of the 21st century. They reached the conclusion that the deregulation gave positive effects on the competition and productivity of the U.S. freight transportation industry. This paper extended their analyses for 10 more years into the 21st century with a publicized dataset of the freight transportation companies and it led to a different conclusion: while the truck sector had the same general result, i.e., the more competitive, the higher TFP as the deregulation progresses, the rail sector yielded a different trend, i.e., the less competitive and the lower TFP in the last 25 years since the abolishment of the ICC

CHAPTER VII

CONCLUSION AND FUTURE RESEARCH

7.1 Conclusion

This study analyzes 41 years of data from the U.S. rail and truck industry sectors in order to find out if there were changes in competition level and its productivity. This study also checks how the level of competition and productivity are after the milestone year of 1995 and in the 21st century. Eliminating the ICC was expected to give the freight transportation industry more economic freedoms to boost up the competition in the market, to increase the efficiency of operations, and to increase productivity of the transportation industry. However, after the ICC abolishment, the rail sector experienced less competition and lower total factor productivity compared to the first 16 years of the deregulated period.

The following are answers to the three research questions mentioned in the introduction section:

Q1: Is there any significant difference in industry competition level in the U.S. freight transportation industry after the ICC was abolished in 1995?

While the mean value of market concentration index of the rail sector in Period 2 is significantly higher than that in Period 1, that of the truck sector in Period 2 is significantly lower than its counterpart in Period 1. Thus, while the rail sector has become less competitive in the last 25 years, the truck sector has become more competitive after the ICC abolished in 1995.

Q2: What relationship exists between the competition level and the industry's labor productivity? Is there any difference between two periods, one with the ICC and the other without the ICC?

The truck sector had a positive correlation between market competition and labor productivity in the first 16 years after the start of deregulation. However, after the ICC abolishment, the correlation between the two is negative in both sectors. Labor productivity in both sectors has risen continuously during the 41 years since 1980, but the both sector markets have become less competitive or stable in the last 25 years after the abolishment of ICC.

Q3: Did the ICC have an impact on the productivity in the U.S. freight transportation industry since 1980, the year of starting economic deregulation, and after 1995, the year of ICC abolishment?

Comparing two periods, while the TFP value of the truck sector had improved by 18% from Period 1 to Period 2, the TFP value of the rail sector was reduced by 8%. Thus, the impact directions of both sectors were different.

In summary, after the abolishment of the ICC, the U.S. truck sector became more competitive and the U.S. train sector became less competitive. After the 1995, the market competition and labor productivity have gone toward opposite directions and there have been no positive relationship between market competition and labor productivity in both sectors. In addition, while the truck sector's TFP value improved through the two periods of deregulation, the rail sector's TFP value became worse since the year 1996.

7.2 Limitation

This study has limitations regarding the output measure and labor input measure. For the output measure, most previous studies (Winston, 1998; Martland, 2012; Schmalensee and Wilson, 2016; Gallamore, 2018) used ton-miles as an output of the freight transportation industry. According to the U.S. Bureau of Transportation Statistics (http://www.bts.gov), a ton-mile is the most frequently used measure of freight transportation output. It is defined as "one ton of freight shipped one mile". Revenue-ton-mile is defined as "the revenue earned for transporting one ton of freight across one mile". Therefore, total revenue-ton-miles is the appropriate measure of freight transportation output in terms of dollar value. However, since total revenue-ton-miles is not available in the annual financial statements of freight transportation companies, RT was used as an output measure in this study. For the labor input measure, when calculating labor productivity and total factor productivity, the number of full-time employees was used as a proxy of labor input, which includes neither contracted workers nor part-time workers. The total number of hours worked, including both full-time and part-time employees, is a more appropriate measure of labor input. Since labor statistics such as the number of hours worked is not available in the annual financial statements, the number of full-time employees was used as an input factor in this study.

7.3 Future Research Direction

In the conclusion section, the author mentioned that after the abolishment of the ICC, the rail sector became less competitive and its total factor productivity became decreased. Because of a duopolistic market situation on either side of the U.S. rail network, the STB monitored and regulated the U.S. rail sector. In the truck sector, the U.S. Federal Highway Administration (USFHA) constructs and maintains the National Highway Systems, on which truck companies are doing their business. But, in the rail sector, the U.S. Class I railroads are owned and maintained by private railroad companies. Therefore, infrastructure ownership is different in both sectors. Compared to the railways of advanced foreign countries such as those in Europe or Asia, the U.S. rail system is not the best system. The U.S. rail tracks have not fully been double rail tracked; also, they have not been nationally electrified. Improving competition and productivity in the rail sector is a long-term project, which needs both investing into rail infrastructure and developing a new policy for market competition. Such decisions require a consensus among policy-makers, transportation companies, and consumers.

The U.S. Department of Transportation (DOT), Bureau of Transportation Statistics (BTS) (2022) has published a report on the Commodity Freight Survey (CFS) and the Freight Analysis Framework (FAF). The FAF was developed with CFS data and out-of-scope data, such as U.S. Census data, and freight flow data in transportation, construction, and retail industries, as well as agricultural and farming industry data. The recent report (U.S. DOT BTS, 2022) was published using 2017 data sources, which were composed of the dollar value and weight of freight flows by origin state/area, destination state/area, transportation modes, and commodity types. For example, the dollar value of 2017 domestic freight flows was $15, 081 billion, including $11,296 billion in truck mode and $227 billion in rail mode. The databases have been collected and developed in every 5th year and they could be useful sources for forecasting freight demands and planning investment for freight transportation infrastructure. In addition, the dollar value of freight flows could be an output measure of the transportation industry for calculating labor productivity and total factor productivity.

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APPENDIX A

STATA COMMAND LIST

5.2 Pooled Regression Model

*** Rail Data Set***

```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Rail") firstrow clear
reg LNRT LNAT LNEMP LNGAS ICC
vif
hettest
```

*** Truck Data Set***

```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Truck-Outlier") firstrow clear
reg LNRT LNAT LNEMP LNGAS ICC
vif
hettest
```

5.3 Residual Analysis

*** Rail Data Set***

```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Rail") firstrow clear
reg LNRT LNAT LNEMP LNGAS ICC
predict resi_rail, residual
summarize resi_rail
corr resi_rail LNAT LNEMP LNGAS ICC, cov
rvfplot
```

*** Truck Data Set***

```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Truck-Outlier") firstrow clear
reg LNRT LNAT LNEMP LNGAS ICC
predict resi_truck, residual
summarize resi_truck
corr resi_truck LNAT LNEMP LNGAS ICC, cov
rvfplot
```

5.4 Panel Data Regression Model

*** Rail Data Set***

```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Rail") firstrow clear
xtset TSN FY, yearly
xtreg LNRT LNAT LNEMP LNGAS ICC, fe
estimate store fe
xtreg LNRT LNAT LNEMP LNGAS ICC, re
estimate store re
hausman fe re, sigmamore
xtreg LNRT LNAT LNEMP LNGAS ICC, fe vce(robust)
```

```
xtreg LNRT LNAT LNEMP LNGAS ICC, re vce(robust)
```
***lrtest ***
```
xtgls LNRT LNAT LNEMP LNGAS ICC, igls panels(heteroskedastic)
estimate store hetero
xtgls LNRT LNAT LNEMP LNGAS ICC, igls
local df=e(N_g) - 1
lrtest hetero ., df(`df')
vif, uncentered
xtserial LNRT LNAT LNEMP LNGAS ICC
```

*** Truck Data Set***
```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Truck-Outlier") firstrow clear
xtset TSN FY, yearly
xtreg LNRT LNAT LNEMP LNGAS ICC, fe
estimate store fe
xtreg LNRT LNAT LNEMP LNGAS ICC, re
estimate store re
hausman fe re, sigmamore
xtreg LNRT LNAT LNEMP LNGAS ICC, fe vce(robust)
xtreg LNRT LNAT LNEMP LNGAS ICC, re vce(robust)
```
***lrtest ***
```
xtgls LNRT LNAT LNEMP LNGAS ICC, igls panels(heteroskedastic)
estimate store hetero
xtgls LNRT LNAT LNEMP LNGAS ICC, igls
local df=e(N_g) - 1
lrtest hetero ., df(`df')
vif, uncentered
xtserial LNRT LNAT LNEMP LNGAS ICC
```

*** 5.5 Panel Data Generalized Least Square Regression ***
*** Rail Data Set***
```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Rail") firstrow clear
xtset TSN FY, yearly
xtgls LNRT LNAT LNEMP LNGAS ICC, corr(ar1) force
xtgls LNRT LNAT LNEMP LNGAS ICC, panel(correlated) corr(ar1) force
```
*** panel must be balanced***

*** Truck Data Set***
```
import excel "D:\2-Research\2022\Data\O-Productivity-2022-0218-V3-Outlier.xlsx",
sheet("File5-LN-Truck-Outlier") firstrow clear
xtset TSN FY, yearly
xtgls LNRT LNAT LNEMP LNGAS ICC, corr(ar1) force
xtgls LNRT LNAT LNEMP LNGAS ICC, panel(correlated) corr(ar1) force
```

*** panel must be balanced***

5.6 Industry-Sector Level Analysis
*** Rail Data Set: Pooled Regression***

```
import excel "D:\2-Research\2022\Data\Industry-Rail.xlsx", sheet("Data") firstrow clear
reg LNRT LNAT LNEMP LNGAS ICC
vif
hettest
destring FY, replace
tsset FY, yearly
dwstat
predict resi_rail, residual
summarize resi_rail
corr resi_rail LNAT LNEMP LNGAS ICC, cov
rvfplot
```

*** Truck Data Set: Pooled Regression***

```
import excel "D:\2-Research\2022\Data\Industry-Truck.xlsx", sheet("Data") firstrow clear
reg LNRT LNAT LNEMP LNGAS ICC
vif
hettest
destring FY, replace
tsset FY, yearly
dwstat
predict resi_truck, residual
summarize resi_truck
corr resi_truck LNAT LNEMP LNGAS ICC, cov
rvfplot
```

*** Panel Generalized Least Square Regression ***
Industry-sector level Data for Rail Sector

```
import excel "D:\2-Research\2022\Data\Industry-Rail.xlsx", sheet("Data") firstrow clear
destring FY, replace
xtset SEC FY, yearly
xtgls LNRT LNAT LNEMP LNGAS ICC
```

Industry-sector level Data for Truck Sector

```
import excel "D:\2-Research\2022\Data\Industry-Truck.xlsx", sheet("Data") firstrow clear
destring FY, replace
xtset SEC FY, yearly
xtgls LNRT LNAT LNEMP LNGAS ICC, panel(correlated) corr(ar1) force
```